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14. ABSTRACT

In order to automatically enhance and restore images, especially those taken from underwater environments where scattering and absorption by the medium strongly influence the imaging results even within short distances, it is critical to have access to an objective measure of the quality of images obtained. This contribution presents an approach to measure the sharpness of an image based on the GSA of detected edges. Images are first decomposed by a wavelet transform to remove random and part medium noises, to augment chances of true edge detection. Sharpness of each edge is then determined by regression to determine the slope between gray-scale values of edge pixels versus locations, which is the tangent of an angle based on grayscale. The overall sharpness of the image is the average of each measured GSAs, weighted by the ratio of the power of the first level decomposition details, to the total power of the image. Adaptive determination of edge widths is facilitated by values associated with image noise variances. To further remove the noise contamination, edge widths less than corresponding noise variances or regression requirement are discarded. Without losing generality while easily expandable, only horizontal edge widths are used in this study. Standard test images as well as those taken from field are used to be compared subjectively. Initial restoration results from field measured underwater images based on this approach.

15. SUBJECT TERMS

image quality, sharpness, restoration, underwater, MCM, WGSA, MTF, wavelet

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Objectively assessing underwater image quality for the purpose of automated restoration

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ABSTRACT

In order to automatically enhance and restore images, especially those taken from underwater environments where scattering and absorption by the medium strongly influence the imaging results even within short distances, it is critical to have access to an objective measure of the quality of images obtained. This contribution presents an approach to measure the sharpness of an image based on the weighted gray-scale-angle (GSA) of detected edges. Images are first decomposed by a wavelet transform to remove random and part medium noises, to augment chances of true edge detection. Sharpness of each edge is then determined by regression to determine the slope between gray-scale values of edge pixels versus locations, which is the tangent of an angle based on grayscale. The overall sharpness of the image is the average of each measured GSAs, weighted by the ratio of the power of the first level decomposition details, to the total power of the image. Adaptive determination of edge widths is facilitated by values associated with image noise variances. To further remove the noise contamination, edge widths less than corresponding noise variances or regression requirement are discarded. Without losing generality while easily expandable, only horizontal edge widths are used in this study. Standard test images as well as those taken from field are used to be compared subjectively. Initial restoration results from field measured underwater images based on this approach and weakness of the metric are also presented and discussed.

Keywords: image quality, sharpness, restoration, underwater, MCM, WGSA, MTF, wavelet

1. BACKGROUND

Image quality has been an interesting and important research subject in digital image processing, especially with the rapid expansion of digital cameras, scanners, and printers into the everyday life of most households in this digital age. Although the term implied a rather broad description of the quality of the image obtained, it is important to understand the scope of the term and the context it is within. When it comes to the image quality, the most common criteria is the sharpness of the image, which represents the ability to present details. This is also referred to as the resolution, and often studied in terms of spatial (angular) frequency. Contrast of an image is closely related to the sharpness or resolution of an image, and usually defined by the differences between lighter and darker areas then divided by the combined brightness [1, 2]. Artifacts and distortions are understandably important parameters in defining image quality as well, especially in medical imaging, but often received little attention in other research areas. The level of noises present in an image can be critical in certain circumstances, especially when the signal-to-noise ratio (SNR) is low, or for the purpose of testing different image compression algorithms.

Like quantifying the performance of an imaging system with a single number, using a single value to describe the quality of an image is at least equally difficult and seemingly impossible, considering the vast differences amongst imaging systems, contents of imageries, and variations in environmental conditions which involve lighting and medium effects. However, the importance and value of a well-defined metric can be tremendous, as part of the computer cognition. The ability of a human being to tell the difference of the image quality in a glimpse is critical in digital image processing, when automation is desired, both for restoration of degraded imageries in post-processing, as well as real-time imaging enhancement. Furthermore, once the ability is passed on to the computer, ie, a dependable metric is defined, vision-enabled robots can go beyond what human can do, such as gaining independence which is important in harsh environments, and perform the same task in much finer precisions and at increased speed.

Understandably, the perceptual image quality is dependent of the individual viewer and so is the value of a metric, but a summation of many opinions often regress to a common ground or a mean opinion score (MOS), which is often used as

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a benchmark for testing the effectiveness of a metric [3]. Mathematical formulas are developed to quantify these perceptual quality metrics such as the perceptual distortion metric (PDM) [4]. This is generally referred to as a subjective metric where human intelligence and cognition is involved, and is often a function of human visual system. An objective image quality metric, on the other hand, aims to establish a measure of image quality regardless of the human vision system response. There are two types of objective approaches. A majority research has been done in the area where one compares a degraded image to an ideal version, or reference, to aid algorithm development, such as those in image compression for encoding and transmission. The common approaches in determining the quality include the use of peak signal-to-noise ratio (PSNR) and the mean square errors (MSE) [3].

For the type of imageries we are interested in, such as field measured underwater imageries, a no-reference, or blind, objective image quality metric is needed, in order to achieve these goals: 1) to define faithfully the quality of an image without *a priori* knowledge in different environment (ie different water optical properties); 2) independent of the content of an image; 3) immune or less sensitive to noises, especially those caused by the multiple scattering in turbid underwater environments. The establishment of such metric is a critical component in the automated image restoration, where the computer system needs to know "when" to stop, and determine if it has found the best result, and if the "best" result is acceptable in a comparable underwater environment.

Different objective image quality metrics exist, but to the authors' knowledge, there is no universal metric that handles all image types well. For example, quality associated with aerial imageries through the atmospheric turbulence taken by a reconnaissance camera will be different from those images taken over a short distance by a camera mounted on a car affected only by motion blur, and while the latter still different from images taking in a turbid underwater environment such as in an estuary or harbor area. It is practical and possible, however, to compose a quality metric for a given environment and task that is well-defined. One good example is the National Imagery Interpretability Scale (NIIRS) and the associated general image quality equation (GIQE) [5]. NIIRS is primarily a metric designed for image quality assessment for satellite-based systems and as its name implied, it focuses on the scale or the ground-sampled distance (GSD). Briefly, other efforts in objective metrics included those that measure the image quality by its sharpness using the gradient or slope of edges [6], by the perceptual blur which measures local blur values based on all edge widths [7], by a variance approach which assumes smoother edges correspond to less variance [8], by the histogram frequency that is associated with non-zero transformed coefficients [9], by the area under MTF to separate high frequency and low frequency contributions [10], via the power spectrum which measures the ratio of high and low frequency energy to the total to reflect details of the image studied [11], and by a wavelet-based perceptual metric that applied a discrete dyadic wavelet transform to obtain edge constraints [12]. The relatively new wavelet transform helps to preserve the edge characteristics, which is especially useful in the situation associated with discontinuities [13].

Degradation of the image quality in a scattering medium has been studied, where atmospheric effects such as turbulence and scattering by aerosols dominate. These studies are mostly focused on modeling the optical transfer function (or modulation transfer function, MTF, when phase information can be neglected), in an effort to restore the images obtained, such as in air reconnaissance or astronomy studies [14, 15]. The scattering behavior is different in the situation of natural waters, where strong forward scattering dominates. Anyone with experiences in coastal waters, especially those inside a harbor, or estuary areas like Mississippi, has a first-hand look at how visibility could quickly reduce to zero in a matter of a few feet. The same applies to regions of strong re-suspensions from the bottom, both in coastal regions as well as in the deep sea. The images obtained under such conditions are often severely degraded or blurred. The extent of such blurring can be described by the MTF of the medium which includes water itself, constituents within such as particulates (both organic and inorganic) [1]. Theoretically, such effects can be reversed by deconvolving the MTF of the medium from the resulting images [2]. In reality, the effectiveness is often hindered by errors associated with the modeling efforts such as MTF and approximations applied with the small angle scattering. The noises from field measurement results are also part of the mix. Additionally, due to the small incremental quality improvements in restoring badly degraded images, it is hard to judge if one restored result is better than the other, which is critical in an automated process. For these reasons, it is necessary to develop a method to determine objectively the quality of resulting image that has closer ties with the environment. This, in turn, can be used to better determine the more specific issues affecting imaging in underwater environment, namely, low lighting thus low signal to noise levels, fluctuations caused by the medium, and multiple scattering contributions.

This approach improves upon previous efforts especially [7, 11, 12]. Recent advance of wavelet research provides an excellent tool for this purpose, as wavelets are multi-resolution in nature. We use wavelet transforms to remove the effect of scattering when locate edges, and further apply the transformed results in restraining the perceptual metric. The medium MTF is preserved via ESF during measurements. Edge profiles are determined by incorporate noise variance introduced by the scattering

2. IMAGE QUALITY METRIC BASED ON THE WEIGHTED GRAYSCALE ANGLE

Our approach is a wavelet-decomposed and denoised, perceptual metric constrained by a power spectrum ratio, and is depicted in Fig. 1. To properly define the sharpness of an image, it is critical to correctly determine the edge profile. Due to the strong scattering of the medium, some photons can be scattered into rather large angles away from the straight path, resulting in low photons count at the ends of the edge, and can be easily classified as "noise". This is in fact the extension or part of the "broadening" of the edge caused by the scattering, therefore preserving these extensions while removing true noise is critical in denoising process. For this reason, denoising is carried out by applying Daubechies wavelets [16], to obtain more consistent result at locating the edges of the image. The edge profiles of the image are then found using the Canny edge algorithm [17].

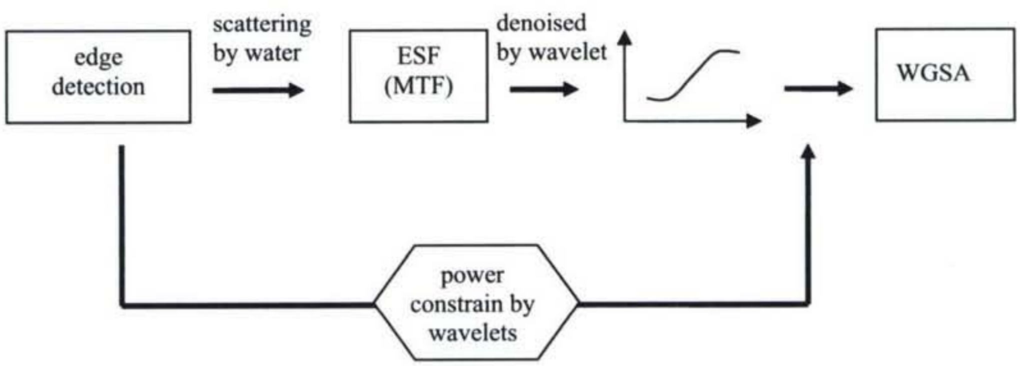

Fig. 1. Outline of the WGSA image quality metric calculation. See text for details.

With the edges located, the program explores to determine the profile of each edge along the horizontal direction, extending to the left and right of the edge pixel determined by the Canny algorithm, which is likely the center of the edge. Considering the randomness of the image contents and its orientation, using edge profiles only at one direction does not invalidate the effectiveness of the approach. To be computationally thrifty, only one out of every 10 edge lines is calculated.

A typical edge profile from an underwater image can be seen in Fig. 2, which is taken from an actual underwater image frame. The edge pixels are determined by the following criteria applied to the original image: the continuous ascending (or descending) in one direction, in grayscale values with a step size in grayscale (SSG) should be no less than a pre-determined value. This pre-determined value is calculated based on the image noise variances using an adaptive Wiener filter approach [18]. This is especially important, as it contains information related to the medium scattering characteristics in order to find the correct edge widths. The resulting profile is essentially the denoised edge spread function (ESF), or in NIIRS terms, the relative edge response (RER) [5], which is directly related to the MTF of the medium.

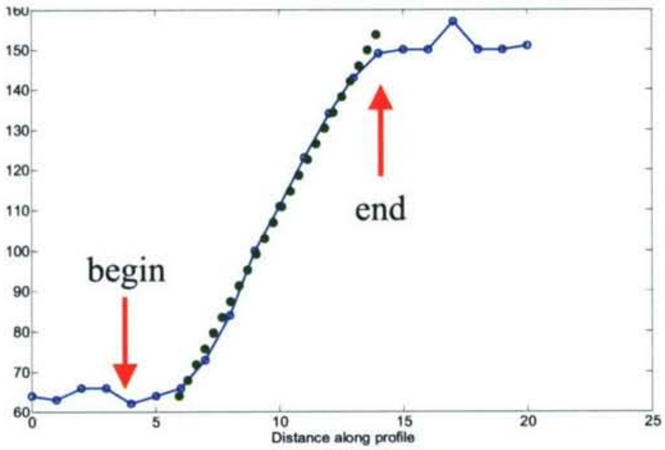

Fig. 2. An image line profile in raw grayscale values from an underwater image frame.

With all the pixels in the edge profile determined, a simple linear regression is applied (Fig.2) to determine the grayscale angle (GSA) of the profile, which determines the raw sharpness of the edge. When all edges are measured, the average value gives the overall measure of the sharpness of the image. Very short edges are excluded from this calculation to avoid contaminations by in-water constituents such as rare large particles or large planktons. An image is declared "edgeless" or not suitable when there are not enough edges found. To properly address the amount of noise (ie high spatial frequency components), and represent different lighting conditions in the underwater environment, it is necessary to introduce a weighting factor that is associated with the power of the image as a function of details. It is found that this is better accomplished by using the ratio between the first-level wavelet decomposed details, to the total power of the original image. Information on wavelet transforms can be found in many references such as [19]. This result is inline with previous power spectrum approach [11].

Applying the above algorithm to an image obtained in a controlled underwater environment (active source, no ambient light, pre-determined absorption and scattering values) [20], the original and the restored version are shown in Figs. 3, with corresponding WGSA values (0.005 and 0.14 respectively). As a comparison, two standard images were used (Fig. 4), one is the original Lena, and the other is a Gaussian blurred version. Their WGSA values are 0.60 and 0.15 respectively. Notice that the blurred version of Lena visually appears better than the restored image in Fig. 3, although they have rather similar WGSA values. This is a good example about the uniqueness amongst different imaging environments. The defined metric has been used in our automated image restoration program, and results demonstrate consistency over more than 30 images tested in different optical conditions and attenuation ranges. In some extreme conditions (eg very low contrast), WGSA will give false values. Another issue with the current approach is the un-even distribution of WGSA values. This is probably the result of two factors. One has to do with the type of wavelets used. The other is related to the pre-set SSG which is associated with noise variances. Different wavelet decomposition approaches can be explored, along with analysis of ESF, to overcome these problems.

3. CONCLUSION

To facilitate the goal to automatically restore degraded imageries obtained from the underwater environment, an image quality metric is defined that is tuned to better respond to the environmental parameters. It is based on the wavelet denoised sharpness, weighted by its normalized power spectrum of decomposed wavelet details. The medium scattering effects are accounted for and treated accordingly in the current approach. Initial results show that the metric defined provides a consistent measure to both the original and improved imageries, and is suitable for automated restoration purposes. Further validation will be carried out using a larger image dataset, such as those similar to NIIRS.

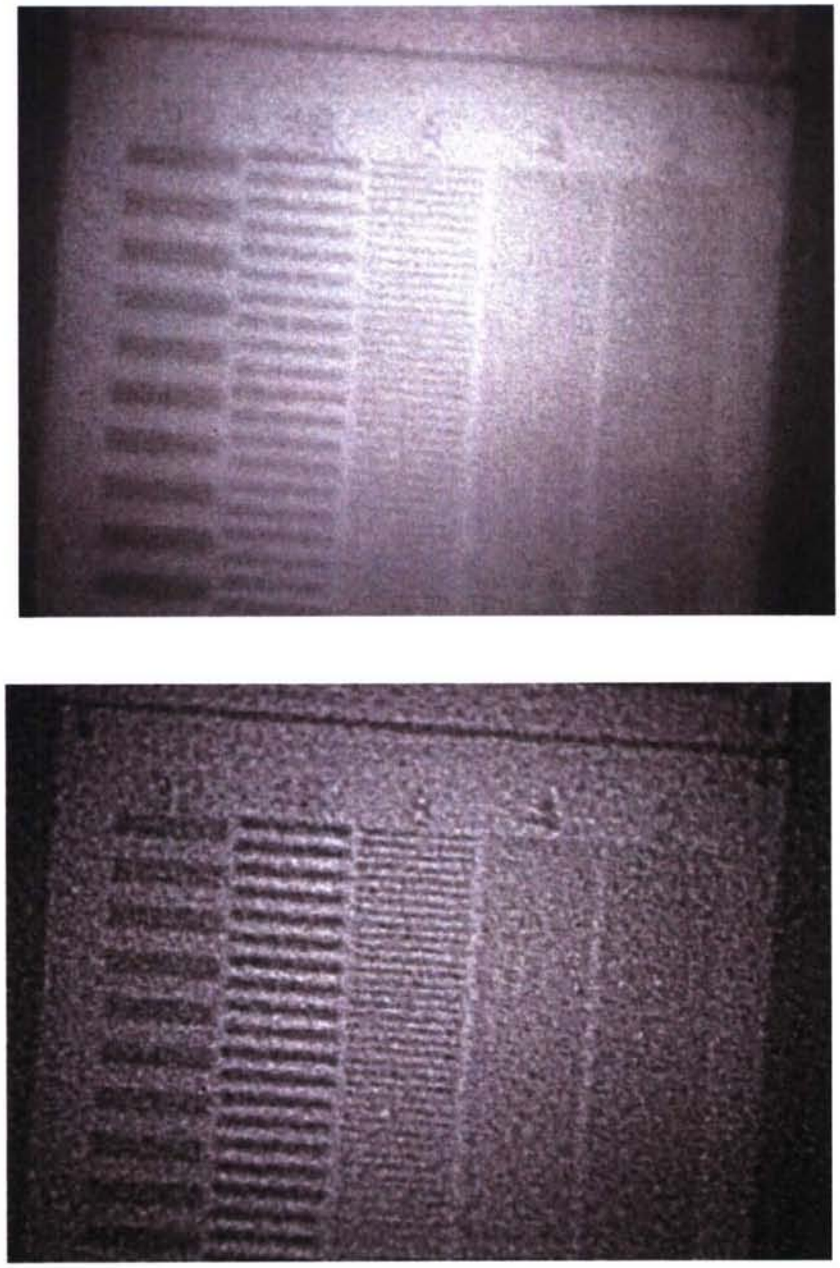

Fig. 3. The original and restored underwater images. The original (top) has WGSA= 0.005 while the restored has a value of 0.14.

Fig. 4. The image quality of Lena and blurred version for comparison. WGSA values are 0.60 and 0.15 respectively.

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